

MORE THAN JUST WIRES: APPLYING COMPLEXITY THEORY TO COMMUNICATION NETWORK ASSURANCE

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Extended Abstract

Complexity Theory is the study of order within otherwise chaotic systems (Holland, 1999). Complexity Theory often focuses on Complex Adaptive Systems (CAS). A CAS is a system of components that interact and reproduce while adapting to their environment. A CAS consists of large numbers of components that are diverse in both form and capability. A CAS exhibits unstable coherence in spite of constant disruptions and a lack of central planning.

Large-scale, interconnected infrastructures such as communication networks are CAS. These infrastructures are vastly more dynamic than their predecessors. Such infrastructures consist of a large number of components and participants that are diverse in both form and capability. Furthermore, these infrastructures exhibit unstable coherence in spite of constant disruptions and a lack of central planning.

Viewing large scale, interconnected infrastructures with complex physical architectures, such as communication networks, as CAS can provide new many insights (Bower and Bunn, 2000; North 2000a, 2000b, and 2001). The CAS approach emphasizes the specific evolution of integrated infrastructures and their participant's behavior, not just simple trends or the end state. The adaptation of the infrastructure participants to changing conditions is paramount. Also, the effects of random events and uncertainty are explicitly considered. One powerful computational approach to understanding CAS is agent-based modeling and simulation (ABMS).

An agent-based model consists of a set of agents and a framework for simulating their decisions and interactions. ABMS is related to a variety of other simulation techniques including discrete event simulation and distributed artificial intelligence or multiagent systems (Law and

Kelton, 2000). While many traits are shared, ABMS is differentiated from these approaches by its focus on achieving “clarity through simplicity” as opposed to deprecating “simplicity in favor of inferential and communicative depth and verisimilitude” (Sallach and Macal, 2001).

Emergent behavior is a key feature of ABMS. Emergent behavior occurs when the behavior of a system is more complicated than the simple sum of the behavior of its components (Holland, 1999). ABMS has been used to study emergent systems as varied as computer networks (Triantafyllopoulos, et. al. 2001), electrical power infrastructures (Bower and Bunn, 2000; North 2000a), equities (LeBaron 1999), foreign exchange (Yang 2000), and integrated economies (Epstein and Axtell, 1996). Furthermore, some of this work involved interdependent systems such as interwoven electrical and natural gas infrastructures (North 2000b, and 2001). Consideration of these examples suggests that ABMS might also be used to study communication networks and the interdependencies between communication networks and other infrastructures such as electrical grids.

Applying ABMS to communication networks and the infrastructures upon which they depend may allow such networks to be understood as more than just wires. Communication networks may then be electronically managed as complete, dynamic systems. An example is the integrated, systems-level computational perspective ABMS has provided to electrical and natural gas infrastructure research (North 2001). This holistic computational perspective may allow both the physical and human dimensions of complex systems such as communication networks to be anticipated and managed online, in real time. Thus, ABMS may be an important tool for developing imperishable networks.

Keywords: Agent-based modeling and simulation, ABMS, Agent-based modeling, ABM, Agent-based simulation, ABS, complex adaptive systems, CAS, telecommunications system modeling.

Introduction

Complexity Theory is the study of order within otherwise chaotic systems (Holland, 1999). ~~Complexity Theory~~ and often focuses on Complex Adaptive Systems (CAS). A CAS is a system of components that interact and reproduce while adapting to their environment. A CAS consists of large numbers of components that are diverse in both form and capability. A CAS exhibits unstable coherence in spite of constant disruptions and a lack of central planning. Modern infrastructures are CAS.

Large-scale, interconnected infrastructures such as communication networks are CAS. These infrastructures are vastly more dynamic than their predecessors. ~~Such infrastructures consist of a large number of components and participants that are diverse in both form and capability. Furthermore, these infrastructures~~ and exhibit unstable coherence in spite of constant disruptions and a lack of central planning. Modeling such infrastructures is a daunting task. The systems employed in any given industry are highly complex, with dynamic feedback and response mechanisms. Through years of technological evolution, the processes and materials that make modern life possible have grown increasingly interconnected. By leveraging the advances in other sectors, individual industries have improved their ability to efficiently compete in the marketplace. Through this leveraging, the nation's infrastructures have coalesced in varying degrees, forming larger interdependent systems.

The effort to model interdependent systems immediately involves formidable challenges. Obtaining a physical system representation in a particular industry is mostly a matter of obtaining the right data and software packages. Much of this information is available in the commercial marketplace. The natural approach to interdependence modeling is to acquire the proper software packages for several industries and to try running them together. However, even if the effort were successful, the resulting model would lack the operators and other decision-makers that affect the commodity or service delivery. After all, these systems are subject to the laws of business, which are constantly changing, as well as the laws of physics, which are generally absolute.

Most large-scale infrastructures are highly interconnected with other infrastructures. Each interconnected infrastructure affects all of the others. For example, the proliferating use of Internet-based controls for electric generators highlights the increasingly interdependent nature of the electric power (EP) and telecommunications (TC) industries.

Corporations and other large organizations, acting within markets, operate infrastructures according to a myriad of marketplace, legal, ~~and~~ regulatory, and financial considerations. How corporations ultimately choose to operate their interdependent infrastructures is as important as the physics that constrain their plans. Simulating these organizational choices in the appropriate physical context is important to better understand large-scale, interconnected infrastructures.

Simulating infrastructures in isolation is beneficial for design, maintenance, and operation. However, considering the importance of interdependencies, more needs to be done. Simulations must examine the relationships between infrastructures as well as the components within a given infrastructure. Simulating these relationships between infrastructures is only the beginning.

The Challenge

A wide variety of tools exist to study physical infrastructures ~~as~~ such as the telecommunications system. These tools generally take an engineering view of a single infrastructure and then simulate either a specific system state or a sequential time series of system states. The simulation results give a strong indication of the allowable states within which the system can operate. In more advanced simulations, highly desirable or even optimal physical states also can be identified on the basis of the known physical constraints of the system. However, understanding an infrastructure ~~as~~ such the telecommunications system as a CAS requires a broader view. In particular, interdependent infrastructures such as the electric power system must also be understood.

Several problems arise in combining existing simulation tools to create broader simulations. Useful tools result from substantial investments of time, money, and intellectual

capital. Unsurprisingly, the best tools tend to be expensive and proprietary. Lashing several such tools together in an interactive environment has proven extremely difficult and woefully inadequate. Interfacing models at this level is much more than merely getting one model to communicate with another. Basic design assumptions and decisions lead to deeply-seated incompatibilities.

Aggregated models presuppose an understanding of system behavior at a gross level. Models constructed to deal with commodity flows between countries cannot easily represent specific commodity streams that contribute to that flow. Likewise, tailored models that address a commodity stream cannot be simply multiplied to represent the total flow. This distinction between behaviors at the microscopic and macroscopic levels is important. When engineering requirements are imposed on the representative model, the challenges grow.

~~The power flow equations provide a viable global approach to solving power transmission problems. Similar equations exist to describe fluid flow through a pipeline. As yet, there is no mathematical description of the combined system. Without an adequate global formulation of the system to be modeled, we are reduced to heuristic estimates of causal response. Such a global formulation would be challenged to address local interactions that are important because they are the essence of infrastructure interdependence.~~

None of the previous techniques are in and of themselves adequate. A new approach that melds the advantages of each of these techniques is needed. CAS may be the answer.

Viewing large scale, interconnected infrastructures with complex physical architectures, such as communication networks, as CAS can provide new many insights (Bower and Bunn, 2000; North 2000a, 2000b, and 2001). The CAS approach emphasizes the specific evolution of integrated infrastructures and their participant's behavior, not just simple trends or the end states. The adaptation of the infrastructure participants to changing conditions is paramount. Also, the effects of random events and uncertainty are explicitly considered. One powerful computational approach to understanding CAS is agent-based modeling and simulation (ABMS).

—An agent-based model consists of a set of agents and a framework for simulating their decisions and interactions. ABMS is related to a variety of other simulation techniques including discrete event simulation and distributed artificial intelligence or multiagent systems (Law and Kelton, 2000). While many traits are shared, ABMS is differentiated from these approaches by its focus on achieving “clarity through simplicity” as opposed to deprecating “simplicity in favor of inferential and communicative depth and verisimilitude” (Sallach and Macal, 2001). It offers the opportunity to gain new insights into the operation of large-scale, interconnected infrastructures and explicitly represents the behaviors of individual decision-makers. An ABS in the infrastructure interdependency context consists of a set of agents and a framework for simulating the agents’ decision-making processes and interactions over time.

Agent simulations that allow agents to have adaptive behaviors often ~~exhibit~~ expose system-wide emergent behaviors. Emergent behavior occurs when a system’s behavior is more complicated than the simple sum of the behaviors of its components. The behavior of large-scale, interconnected infrastructures is more complicated than the simple sum of their component’s behaviors when the market decision-making behavior is coupled with the physical operations of the components. Furthermore, modern infrastructures exhibit coherence in spite of constant disruptions and a lack of central planning. Traditional simulation techniques such as linear programming do not include emergent behavior, ~~but~~; ABMS emphasizes it. Many insights can be gained by viewing the ~~new energy~~ telecommunications market from the ABMS-emergent-behavior perspective.

A conscious focus on dynamics is one of the major differences between ABMS and more traditional approaches. This focus on dynamics gives ABMS modelers an enhanced ability to investigate change. To be effective, this enhanced ability must be coupled with increased attention to “dynamic stability.” Most actual large-scale systems are moderately stable until they reach some form of crisis. However, this dynamic stability is often chaotic and unpredictable.

Creating models of these systems requires careful attention to the “forces” that contribute to the dynamic stability.

[Emergent behavior is a key feature of ABMS. Emergent behavior occurs when the behavior of a system is more complicated than the simple sum of the behavior of its components (Holland, 1999). Emergent behavior is sometimes called “swarm intelligence”, since it often arises from a group of individuals cooperating to solve a common problem (Bonabeau, Dorigo, and Theraulaz, 1999). Diversity drives swarm intelligence and provides a source for new ideas or approaches. The key is to balance the level of diversity. Too little diversity leads to stagnation. Too much diversity prevents exploitation of existing good ideas. Achieving a balance between these extremes of diversity is crucial to system survival. The infrastructure simulation will allow exploration of emergent behavior and provide insights into the ways that individual organizations influence their markets, as well as how each market influences its participants. These insights can enhance the understanding and management of infrastructure interdependence.]

Complex Adaptive Systems

The nature of how emergent properties arise in systems and of how systems adapt over time is being studied in the field of complexity theory. CAS is the area most relevant to modeling interdependent infrastructures. A CAS, operating under high stress conditions, can be close to a breaking point at which any additional stress results in a dramatic change in the behavior of the system. The system undergoes what is akin to a phase-change in a physical system ~~or an~~ “avalanche” effect and shifts to a drastically different state (Sole, and Goodwin, 2000).

Holland has analyzed CAS extensively and drawn conclusions on their common characteristics (Holland, 1995). He has identified seven basic features common to all CAS – four properties (aggregation, nonlinearity, flows, and diversity) and three mechanisms for change (tagging, internal models, and building blocks). Any CAS simulation model of interdependent infrastructures should emphasize these features.

Other aspects of CAS have relevance to the development of agent-based models of the infrastructure. The environment surrounding an agent can act as a dominant state variable that structures and sequences the agent's behavior (Bonabeau, Dorigo, and Theraulaz, 1999). Thus, the agent's memory is composed of the agent's own storage capacity plus that of the environment. This situation echoes the declarative approach in the sense that agents must have a discrete set of rules that are activated when appropriate environmental cues occur. The environment structures an agent's behavior; e.g., [an ant adding to an anthill](#). For example, consider ants building an anthill. The new work ~~the~~ any ant does is prompted by the existing layout of the hill. This work modifies the anthill, resulting in a feedback loop. The critical issue is feedback that allows the environment to be part of an agent's "memory."

The Components: Agents

[Modern infrastructures consist of a large number of participants (agents) that are diverse in both form and capability. Participants are both physical and economic in nature, and they have input, output, and decision-making capability. Economic participants include energy and transmission companies and consumers. Specifically, economic agents of the EP system include independent system operators, real-time dispatchers, demand aggregators, customers, generation companies, power generators, transmission companies, and regulators. Decision-makers can be characterized as having different objectives and constraints with a limited ability to process information. They receive incomplete information and have a limited (dynamic) set of choices. In the physical system, physical components are regarded as agents, but economic factors and policy set the environment in which they operate.]

An agent in the simulation, as defined here, is a software representation of a "decision-making" unit. Following Holland, an agent's behavior is modeled with a set of simple decision rules that are able to change and adapt over time in response to repeated interactions with other agents and with the environment. The interactions among individual agents may be simple, but

the complex chains of interdependencies among agents may result in counter-intuitive, unpredictable, and chaotic patterns of system behavior.

Adaptation, in the biological sense, is the process whereby an organism adjusts itself to its environment. In an agent simulation, an agent can adapt by changing its rules with experience, thereby positioning itself to better fit its environment. If agents do not learn or are unable to adapt quickly enough to a changing environment, they can be replaced by others likely to perform better. This is social learning versus individual learning. Both aspects of learning would be present in a CAS model of agent representation for the EP and NG infrastructures. Agents are specialized software-engineering objects possessing some form of intelligence or self-direction (Booch, 1994).

ABMS has been used to study emergent systems as varied as computer networks (Triantafyllopoulos, et. al. 2001), electrical power infrastructures (Bower and Bunn, 2000; North 2000a), equities (LeBaron 1999), foreign exchange (Yang 2000), and integrated economies (Epstein and Axtell, 1996). Furthermore, some of this work involved interdependent systems such as interwoven electrical and natural gas infrastructures (North 2000b, and 2001). Consideration of these examples suggests that ABMS might also be used to study communication networks and the interdependencies between communication networks and other infrastructures such as electrical grids.

Temporal Issues

A particular technical challenge of modeling combined infrastructures is the treatment of time. System behavior is determined by decisions made over a variety of time scales, and the creation of agent models that cover the full range of time scales is critical to understanding complex infrastructure interdependencies. Human economic decision-making dominates longer time scales while physical laws dominate shorter time scales. The focus of each agent's rules varies to match the time scale in which it operates.

Model of Interdependent Infrastructures

A model of interdependent TC and EP infrastructures might contain five layers, one for each of the physical infrastructures, one for each of the corresponding industries, and a consumer layer that is common to all infrastructures. The infrastructure layers would contain physical network models; e.g., EP nodes (generating units, power plants, transformer stations, and distribution stations) and EP links (transmission lines); and TC nodes (telephones, PBXs, and switches) and TC links (telecommunications lines). Not every physical component would be modeled in the infrastructures; rather, the physical infrastructure would be modeled only to the level of detail required to reproduce aggregate system features, such as total energy flow, at a reasonable level of accuracy.

The EP and TC industrial layers would consist of the decision-making entities within these respective industries. The industry layers are where the identities of agents are established on the basis of economic considerations. Financial decisions regarding the operation of and investment in the respective infrastructures are made at this level on the basis of revenues from consumers.

In addition to the financial realm, interdependencies also arise in the form of the physical connections; e.g., (the EP industry is using increasing amounts of telecommunications capacity for systems control). Modeling the financial and energy flows in this way allows for the formation of the feedback loops that could exist between these infrastructures. It also allows for explicit accounting of financial as well as other resources, giving an indication of the organizational possibilities for survival, growth, acquisition, and bankruptcy within the industry.

A distinct advantage of a combined model is the reduction of bias associated with the constituent disciplines. A telecommunications engineer could give a credible response to the impact of a telephone line failure on the physical system, but he would be hard-pressed to address the subsequent market response of consumers in any detail. Similarly, a broker in the EP market would make transactional decisions on the basis of a variety of factors, including reduced supply, but could not be expected to fully comprehend the pipeline or power generator operational

responses.) However, a model that provided sufficient environmental stimuli to each one of these decision-makers would permit each to respond in his element. With adequate linkages, events could ripple through both the physical and the financial realms.

The complexity of modern systems and markets leads to the need to model both the physical and financial infrastructures in the environment defined by policy. The potential usefulness as a policy-testing platform is alluring. To have a model that captures both engineering and market constraints allows a wide variety of policy questions to be explored before implementation. Adjustments in the behavioral rules for one class of decision-makers could have significant physical and financial impacts. Market shifts that create high demand for a particular commodity could be stymied by insufficient capacity to meet that demand. This imbalance would feed back into the market with unpredictable results, depending on available alternatives. Thus, local interactions can have system-wide impact.

Another advantage of a combined model is the exploration of a larger range of possible responses. While not predictive, such a model could expose potential behaviors that would not otherwise be considered. The model is not constrained in its ability to adapt to new circumstances. Perhaps not all observed model behaviors would be immediately explainable. But, the observation of these behaviors in a reasonable model forces one to consider the possible responses.

Conclusion

Applying ABMS to communication networks and the infrastructures upon which they depend may allow such networks to be understood as more than just wires. Communication networks may then be electronically managed as complete, dynamic systems. An example is the integrated, systems-level computational perspective ABMS has provided to electrical and natural gas infrastructure research (North 2001). This holistic computational perspective may allow both the physical and human dimensions of complex systems such as communication networks to be

anticipated and managed online, in real time. Thus, ABMS may be an important tool for developing imperishable networks.

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